Assignment 7: GLMs (Linear Regressios, ANOVA, & t-tests)

Laila Abed

Fall 2024

OVERVIEW

This exercise accompanies the lessons in Environmental Data Analytics on generalized linear models.

Directions

1. Rename this file `<FirstLast>_A07_GLMs.Rmd` (replacing `<FirstLast>` with your first and last name).
2. Change "Student Name" on line 3 (above) with your name.
3. Work through the steps, **creating code and output** that fulfill each instruction.
4. Be sure to **answer the questions** in this assignment document.
5. When you have completed the assignment, **Knit** the text and code into a single PDF file.

Set up your session

1. Set up your session. Check your working directory. Load the tidyverse, agricolae and other needed packages. Import the *raw* NTL-LTER raw data file for chemistry/physics (`NTL-LTER_Lake_ChemistryPhysics_Raw.csv`). Set date columns to date objects.

2. Build a ggplot theme and set it as your default theme.

```
#1

#Loading libraries and reading CVS processed datasets.
library(tidyverse);library(agricolae);library(here)
```

```
## -- Attaching core tidyverse packages ------------------------ tidyverse 2.0.0 --
## v dplyr     1.1.4     v readr     2.1.5
## v forcats   1.0.0     v stringr   1.5.1
## v ggplot2   3.5.1     v tibble    3.2.1
## v lubridate 1.9.3     v tidyr     1.3.1
## v purrr     1.0.2
## -- Conflicts ------------------------------------------ tidyverse_conflicts() --
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()    masks stats::lag()
## i Use the conflicted package (<http://conflicted.r-lib.org/>) to force all conflicts to become errors
## here() starts at /home/guest/EDE_Fall2024
```

```r
here()
```

```
## [1] "/home/guest/EDE_Fall2024"
```

```r
getwd()
```

```
## [1] "/home/guest/EDE_Fall2024"
```

```r
raw_data <-
  read.csv(here(
"./Data/Raw/NTL-LTER_Lake_ChemistryPhysics_Raw.csv"
), stringsAsFactors = TRUE)

# Convert the "sampledate" to date
raw_data$sampledate <- as.Date(raw_data$sampledate, format = "%m/%d/%y")
# Check if sample date is date now
class(raw_data$sampledate)
```

```
## [1] "Date"
```

```r
#2
# Define my custom ggplot theme
library(ggplot2)
custom_theme <- theme_minimal() +
theme(
text = element_text(size = 12, color = "black"),
axis.title = element_text(face = "bold"),
axis.text = element_text(color = "blue"),
panel.background = element_rect(fill = "lightgray"),
panel.grid.major = element_line(color = "gray"),
panel.grid.minor = element_blank()
)
# Set my custom theme as the default theme
theme_set(custom_theme)
```

Simple regression

Our first research question is: Does mean lake temperature recorded during July change with depth across all lakes?

3. State the null and alternative hypotheses for this question: > Answer: H0:There is no significant change in mean lake temperature recorded during July with depth across all lakes. Ha: There is a significant change in mean lake temperature recorded during July with depth across all lakes.

4. Wrangle your NTL-LTER dataset with a pipe function so that the records meet the following criteria:

- Only dates in July.
- Only the columns: `lakename`, `year4`, `daynum`, `depth`, `temperature_C`
- Only complete cases (i.e., remove NAs)

5. Visualize the relationship among the two continuous variables with a scatter plot of temperature by depth. Add a smoothed line showing the linear model, and limit temperature values from 0 to 35 °C. Make this plot look pretty and easy to read.

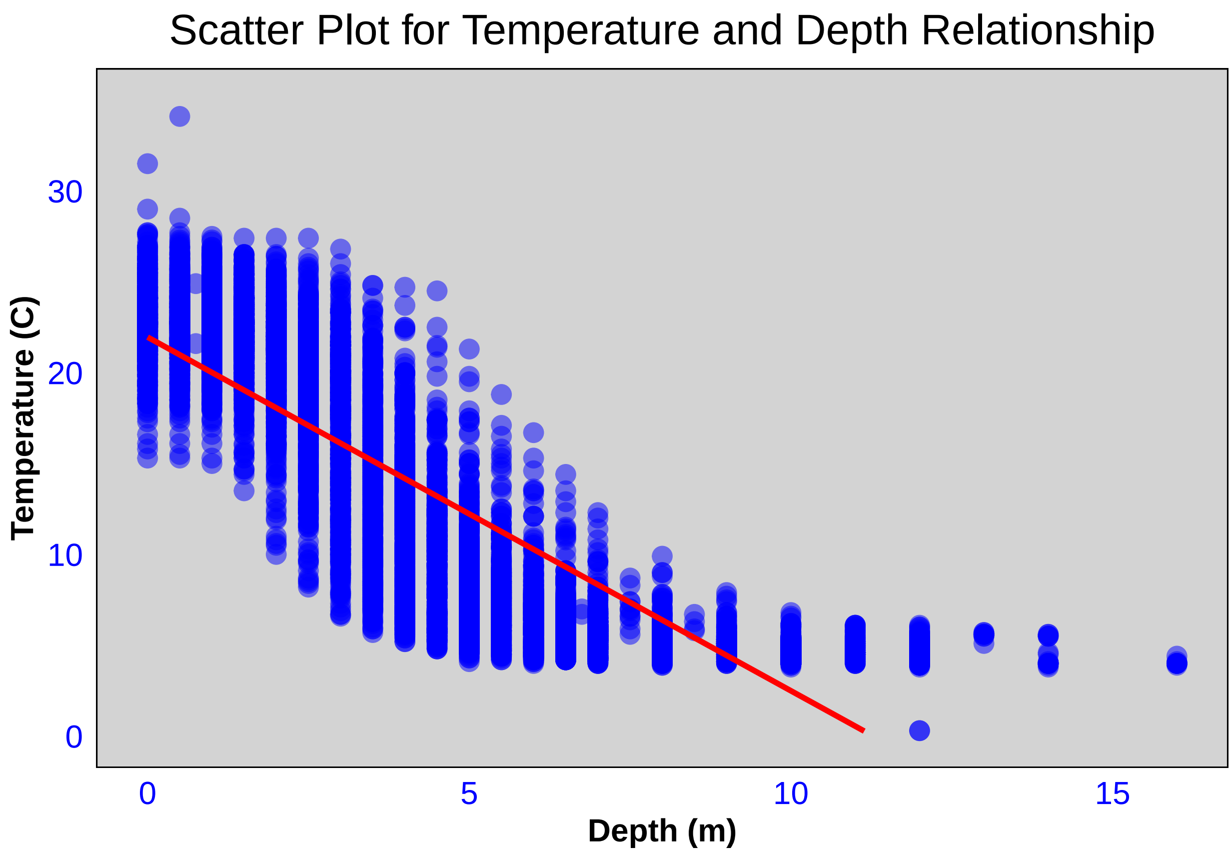
```
#4
#Load the dplyr and tidyr packages
library(dplyr)
library(tidyr)
# Filter records with dates in July, select columns "lakename, year4, daynum,
# depth, temperature_C", and remove NAs.
filtered_data <- raw_data %>%
filter(format(sampledate, "%m") == "07") %>%
select(lakename, year4, daynum, depth, temperature_C) %>%
drop_na()
# View the head of the filtered dataset
head(filtered_data)
```

```
##    lakename year4 daynum depth temperature_C
## 1 Paul Lake  1984    183   0.0          22.8
## 2 Paul Lake  1984    183   0.5          22.9
## 3 Paul Lake  1984    183   1.0          22.8
## 4 Paul Lake  1984    183   1.5          22.7
## 5 Paul Lake  1984    183   2.0          21.7
## 6 Paul Lake  1984    183   2.5          20.3
```

```
#5
# Load the ggplot2 package
library(ggplot2)
# Create a scatter plot with a smoothed line
scatter_plot <-
  ggplot(data = filtered_data, aes(x = depth, y = temperature_C)) +
geom_point(color = "blue", size = 3, alpha = 0.5) +
geom_smooth(method = "lm", se = FALSE, color = "red") +
# Customize the plot's appearance
labs(
title = "Scatter Plot for Temperature and Depth Relationship",
x = "Depth (m)",
y = "Temperature (C)"
) +
#theme_minimal() +
theme(
panel.grid.major = element_blank(),
panel.grid.minor = element_blank(),
axis.title = element_text(face = "bold"),
axis.text = element_text(size = 12),
plot.title = element_text(size = 16, hjust = 0.5)
) +
ylim(0, 35)
# Display the scatter plot
scatter_plot
```

```
## `geom_smooth()` using formula = 'y ~ x'
```

```
## Warning: Removed 24 rows containing missing values or values outside the scale range
## (`geom_smooth()`).
```



6. Interpret the figure. What does it suggest with regards to the response of temperature to depth? Do the distribution of points suggest about anything about the linearity of this trend?

   Answer: There is a negative linear relationship between depth and temperature. As depth increases, the temperature tends to decrease.

7. Perform a linear regression to test the relationship and display the results.

```
#7
# Linear regression model
linear_model <- lm(temperature_C ~ depth, data = filtered_data)
# Display the summary of the linear regression model
summary(linear_model)
```

```
##
## Call:
## lm(formula = temperature_C ~ depth, data = filtered_data)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -9.5173 -3.0192  0.0633  2.9365 13.5834
```

```
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) 21.95597    0.06792   323.3   <2e-16 ***
## depth       -1.94621    0.01174  -165.8   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 3.835 on 9726 degrees of freedom
## Multiple R-squared:  0.7387, Adjusted R-squared:  0.7387
## F-statistic: 2.75e+04 on 1 and 9726 DF,  p-value: < 2.2e-16
```

8. Interpret your model results in words. Include how much of the variability in temperature is explained by changes in depth, the degrees of freedom on which this finding is based, and the statistical significance of the result. Also mention how much temperature is predicted to change for every 1m change in depth.

   Answer: The linear regression model shows that there is a significant change in mean lake temperature recorded during July with depth across all lakes. Meaning changes in depth has a significant change in the lake temperature (negative relationship as depth increases, temperature decreases), accounting for nearly (R sequare) 74% of the variability (74% of the variability in temperature can be explained by changes in depth).
   The model is based on 9,726 data points (big sample size so it is very represenetaive to the population) and indicates a relationship between temperature and depth that is statistically significant. The p-values for both the intercept and slope of the depth are less than 0.05, indicating that these results are statistically significant at any conventional level. This suggests that for every 1-meter increase in depth, the temperature will decrease by approximately 1.946 degrees Celsius, as predicted by the estimated slope of the depth variable. Residual standard error: 3.835 on 9726 degrees of freedom.

Multiple regression

Let's tackle a similar question from a different approach. Here, we want to explore what might the best set of predictors for lake temperature in July across the monitoring period at the North Temperate Lakes LTER.

9. Run an AIC to determine what set of explanatory variables (year4, daynum, depth) is best suited to predict temperature.

10. Run a multiple regression on the recommended set of variables.

```
#9
# Create a list of models with different combinations of predictor variables
models <- list(
model1 = lm(temperature_C ~ year4, data = filtered_data),
model2 = lm(temperature_C ~ daynum, data = filtered_data),
model3 = lm(temperature_C ~ depth, data = filtered_data),
model4 = lm(temperature_C ~ year4 + daynum, data = filtered_data),
model5 = lm(temperature_C ~ year4 + depth, data = filtered_data),
model6 = lm(temperature_C ~ daynum + depth, data = filtered_data),
```

```r
model7 = lm(temperature_C ~ year4 + daynum + depth, data = filtered_data)
)
model7 = lm(temperature_C ~ year4 + daynum + depth, data = filtered_data)
step(model7)
```

```
## Start:  AIC=26065.53
## temperature_C ~ year4 + daynum + depth
##
##          Df Sum of Sq    RSS   AIC
## <none>                141687 26066
## - year4   1       101 141788 26070
## - daynum  1      1237 142924 26148
## - depth   1    404475 546161 39189
```

```
##
## Call:
## lm(formula = temperature_C ~ year4 + daynum + depth, data = filtered_data)
##
## Coefficients:
## (Intercept)        year4       daynum        depth
##    -8.57556      0.01134      0.03978     -1.94644
```

```r
# Calculate AIC for each model
AIC_values <- sapply(models, AIC)
# Find the model with the lowest AIC
best_model <- names(AIC_values)[which.min(AIC_values)]
# Display AIC values and the best model
AIC_values
```

```
##   model1   model2   model3   model4   model5   model6   model7
## 66819.14 66796.54 53762.12 66798.34 53756.97 53679.36 53674.39
```

```r
#10
# Multiple regression model with year4, daynum, and depth as predictors
multiple_regression_model <- lm(temperature_C ~ year4 + daynum + depth, data = filtered_data)
# Display the summary of the multiple regression model
summary(multiple_regression_model)
```

```
##
## Call:
## lm(formula = temperature_C ~ year4 + daynum + depth, data = filtered_data)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -9.6536 -3.0000  0.0902  2.9658 13.6123
##
## Coefficients:
##              Estimate Std. Error  t value Pr(>|t|)
## (Intercept) -8.575564   8.630715   -0.994  0.32044
## year4        0.011345   0.004299    2.639  0.00833 **
## daynum       0.039780   0.004317    9.215  < 2e-16 ***
```

```
## depth       -1.946437   0.011683 -166.611  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 3.817 on 9724 degrees of freedom
## Multiple R-squared:  0.7412, Adjusted R-squared:  0.7411
## F-statistic:  9283 on 3 and 9724 DF,  p-value: < 2.2e-16
```

11. What is the final set of explanatory variables that the AIC method suggests we use to predict temperature in our multiple regression? How much of the observed variance does this model explain? Is this an improvement over the model using only depth as the explanatory variable?

    Answer: The AIC method uses variables (year4, daynum, and depth) to predict temperature variability in the North Temperate Lakes LTER data. These variables provide the best predictors for explaining temperature changes, and the three of them explain 74.12% of the varability of temperature. By comparing the model that uses all three variables with the model that uses only depth, we found that the model with all three variables provides an improvement in explaining temperature variability. This suggests that year4 and daynum provide additional information to the prediction of temperature beyond what can be explained by depth alone. The model including all three variables is better at explaining temperature varability than the model with only depth, which explains 73.87% of the temperature varability.

Analysis of Variance

12. Now we want to see whether the different lakes have, on average, different temperatures in the month of July. Run an ANOVA test to complete this analysis. (No need to test assumptions of normality or similar variances.) Create two sets of models: one expressed as an ANOVA models and another expressed as a linear model (as done in our lessons).

```r
#12
# ANOVA test to compare mean temperatures among lakes
anova_model <- aov(temperature_C ~ lakename, data = filtered_data)
# Display the summary of ANOVA
summary(anova_model)
```

```
##               Df Sum Sq Mean Sq F value Pr(>F)
## lakename       8  21642  2705.2      50 <2e-16 ***
## Residuals   9719 525813    54.1
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
# Fit a linear model with lakename as a predictor
linear_model_lakes <- lm(temperature_C ~ lakename, data = filtered_data)
# Display the summary of the linear model
summary(linear_model_lakes)
```

```
##
## Call:
## lm(formula = temperature_C ~ lakename, data = filtered_data)
```

```
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -10.769  -6.614  -2.679   7.684  23.832
##
## Coefficients:
##                          Estimate Std. Error t value Pr(>|t|)
## (Intercept)               17.6664     0.6501  27.174  < 2e-16 ***
## lakenameCrampton Lake     -2.3145     0.7699  -3.006 0.002653 **
## lakenameEast Long Lake    -7.3987     0.6918 -10.695  < 2e-16 ***
## lakenameHummingbird Lake  -6.8931     0.9429  -7.311 2.87e-13 ***
## lakenamePaul Lake         -3.8522     0.6656  -5.788 7.36e-09 ***
## lakenamePeter Lake        -4.3501     0.6645  -6.547 6.17e-11 ***
## lakenameTuesday Lake      -6.5972     0.6769  -9.746  < 2e-16 ***
## lakenameWard Lake         -3.2078     0.9429  -3.402 0.000672 ***
## lakenameWest Long Lake    -6.0878     0.6895  -8.829  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 7.355 on 9719 degrees of freedom
## Multiple R-squared:  0.03953,    Adjusted R-squared:  0.03874
## F-statistic:    50 on 8 and 9719 DF,  p-value: < 2.2e-16
```

13. Is there a significant difference in mean temperature among the lakes? Report your findings.

    Answer: Yes, there is a significant difference in mean temperature among the lakes for July. Both the ANOVA test and the linear model provided evidence of the significant difference. The ANOVA results showed that the p-value is less than 0.05, which is statistically significant. This indicates that at least one lake has a different mean temperature from the others. Also, the linear model showed that the p-values for each lake (compared to the reference lake) are less than 0.05 indicating that the differences in mean temperatures for each lake are statistically significant.

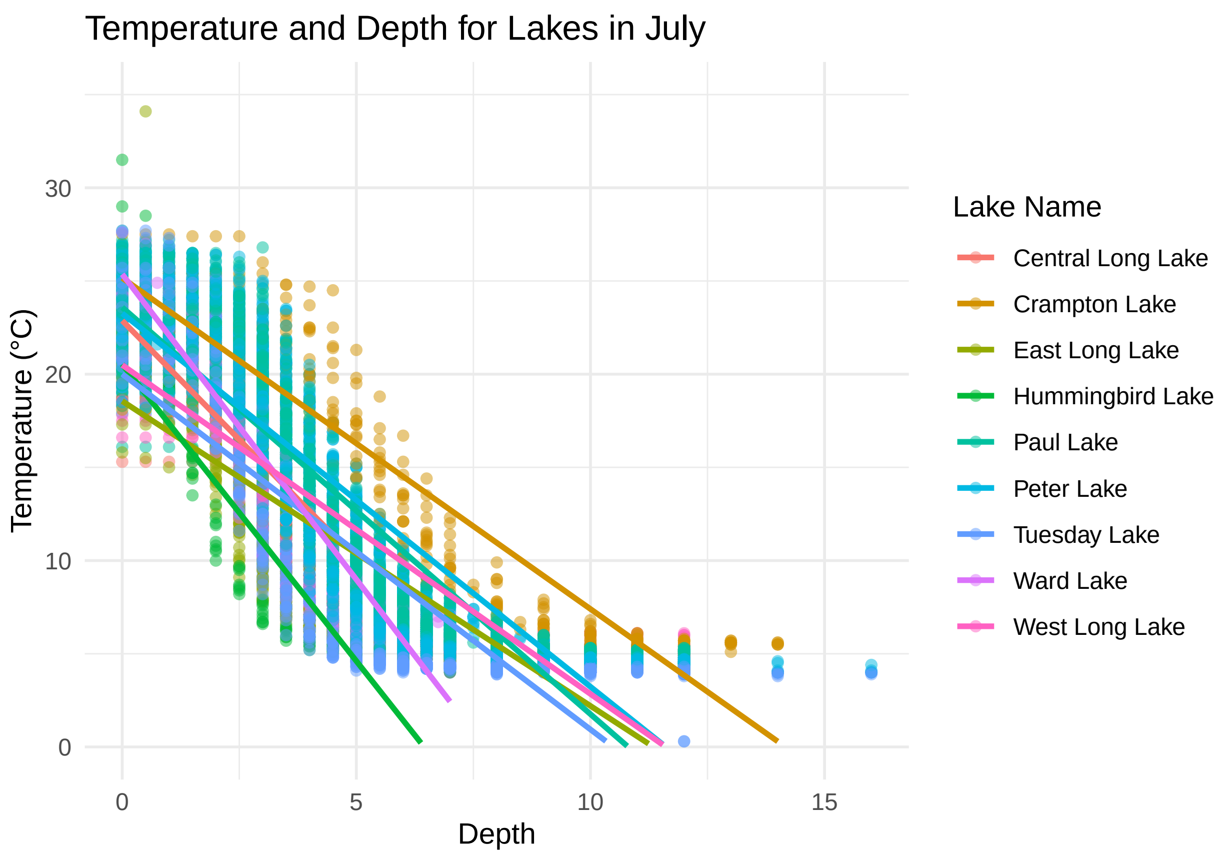
14. Create a graph that depicts temperature by depth, with a separate color for each lake. Add a geom_smooth (method = "lm", se = FALSE) for each lake. Make your points 50 % transparent. Adjust your y axis limits to go from 0 to 35 degrees. Clean up your graph to make it pretty.

```r
#14.

# Create the scatter plot with separate colors for each lake
ggplot(filtered_data, aes(x = depth, y = temperature_C, color = lakename)) +
geom_point(alpha = 0.5) +
geom_smooth(method = "lm", se = FALSE) +
ylim(0, 35) +
labs(
x = "Depth",
y = "Temperature (°C)",
title = "Temperature and Depth for Lakes in July",
color = "Lake Name"
) +
theme_minimal()
```

```
## `geom_smooth()` using formula = 'y ~ x'
```

```
## Warning: Removed 73 rows containing missing values or values outside the scale range
## (`geom_smooth()`).
```



15. Use the Tukey's HSD test to determine which lakes have different means.

```
#15

library(stats)
# Tukey's HSD test to compare means of different lakes
tukey_result <- HSD.test(aov(temperature_C ~ lakename, data = filtered_data),"lakename", group = T)
# Print
print(tukey_result)
```

```
## $statistics
##    MSerror   Df     Mean       CV
##    54.1016 9719 12.72087 57.82135
##
## $parameters
##    test    name.t ntr StudentizedRange alpha
##    Tukey lakename   9         4.387504  0.05
##
## $means
##                     temperature_C      std    r        se Min  Max    Q25   Q50
## Central Long Lake        17.66641 4.196292  128 0.6501298 8.9 26.8 14.400 18.40
## Crampton Lake            15.35189 7.244773  318 0.4124692 5.0 27.5  7.525 16.90
```

```
## East Long Lake         10.26767 6.766804  968 0.2364108 4.2 34.1  4.975  6.50
## Hummingbird Lake       10.77328 7.017845  116 0.6829298 4.0 31.5  5.200  7.00
## Paul Lake              13.81426 7.296928 2660 0.1426147 4.7 27.7  6.500 12.40
## Peter Lake             13.31626 7.669758 2872 0.1372501 4.0 27.0  5.600 11.40
## Tuesday Lake           11.06923 7.698687 1524 0.1884137 0.3 27.7  4.400  6.80
## Ward Lake              14.45862 7.409079  116 0.6829298 5.7 27.6  7.200 12.55
## West Long Lake         11.57865 6.980789 1026 0.2296314 4.0 25.7  5.400  8.00
##                       Q75
## Central Long Lake 21.000
## Crampton Lake     22.300
## East Long Lake    15.925
## Hummingbird Lake  15.625
## Paul Lake         21.400
## Peter Lake        21.500
## Tuesday Lake      19.400
## Ward Lake         23.200
## West Long Lake    18.800
##
## $comparison
## NULL
##
## $groups
##                   temperature_C groups
## Central Long Lake      17.66641      a
## Crampton Lake          15.35189     ab
## Ward Lake              14.45862     bc
## Paul Lake              13.81426      c
## Peter Lake             13.31626      c
## West Long Lake         11.57865      d
## Tuesday Lake           11.06923     de
## Hummingbird Lake       10.77328     de
## East Long Lake         10.26767      e
##
## attr(,"class")
## [1] "group"
```

16.From the findings above, which lakes have the same mean temperature, statistically speaking, as Peter Lake? Does any lake have a mean temperature that is statistically distinct from all the other lakes?

> Answer:The results of the statistical analysis show that the temperature of Peter Lake is significantly different from Crampton Lake, East Long Lake, Hummingbird Lake, Tuesday Lake and West Long Lake. The adjusted p-value for the comparison between Peter Lake and Crampton Lake is less than 0.05, indicating a statistically significant difference in their means. Also, the adjusted p-value for the comparison between Peter Lake and Hummingbird Lake is also less than 0.05, showing a statistically significant difference in means. However, there is no statistically significant difference in means between Peter Lake and Paul Lake or between Peter Lake and Ward Lake. The adjusted p-value for the comparison between Peter Lake and Paul Lake; and Peter Lake and Ward Lake are greater than 0.05. This indicates that their means are not statistically different.

17. If we were just looking at Peter Lake and Paul Lake. What's another test we might explore to see whether they have distinct mean temperatures?

    Answer: We can do two samples t-test to compare the mean temperatures of Peter Lake and Paul Lake and determine whether they have distinct mean temperatures.

18. Wrangle the July data to include only records for Crampton Lake and Ward Lake. Run the two-sample T-test on these data to determine whether their July temperature are same or different. What does the test say? Are the mean temperatures for the lakes equal? Does that match you answer for part 16?

```r
# Subset the data for Crampton Lake and Ward Lake
crampton_lake_data <- filtered_data[filtered_data$lakename == "Crampton Lake", "temperature_C"]
ward_lake_data <- filtered_data[filtered_data$lakename == "Ward Lake", "temperature_C"]
# A two-sample t-test
t_test_result <- t.test(crampton_lake_data, ward_lake_data)
# Print the t-test result
print(t_test_result)
```

```
##
##  Welch Two Sample t-test
##
## data:  crampton_lake_data and ward_lake_data
## t = 1.1181, df = 200.37, p-value = 0.2649
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
##  -0.6821129  2.4686451
## sample estimates:
## mean of x mean of y
##  15.35189  14.45862
```

> Answer: Two-Sample t-test indicates: 1. The test does not provide enough evidence to conclude that the mean temperatures for Crampton Lake and Ward Lake in July are significantly different. P-value is greater than 0.05. 2. The null hypothesis that the mean temperatures of Crampton Lake and Ward Lake are equal cannot be rejected based on the t-test. This result does not match the answer for part 16, which suggested that there were statistically significant differences in mean temperatures between lakes based on Tukey's HSD test. In part 16, it was concluded that Peter Lake had the same mean temperature, statistically, as Paul Lake and Ward Lake. However, the t-test result for Crampton Lake and Ward Lake in part 18 suggests that their mean temperatures are not statistically distinct. The difference in results between part 16 and part 18 may be due to the different statistical tests used and their assumptions. Tukey's HSD test considers multiple pairwise comparisons among lakes, while the t-test focuses on a specific comparison between two lakes. Additionally, the t-test used a Welch correction to account for unequal variances, which can affect the results. These differences highlight the importance of choosing appropriate statistical tests and considering the specific research question and data characteristics.